

Predictive Modeling of Opinion and Connectivity Dynamics in Social Networks

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Abstract

Recent years saw an increased interest in modeling and understanding the mechanisms of opinion and innovation spread through human networks. Using analysis of real-world social data, researchers are able to gain a better understanding of the dynamics of social networks and subsequently model the changes in such networks over time. We developed a social network model that both utilizes an agent-based approach with a dynamic update of opinions and connections between agents and reflects opinion propagation and structural changes over time as observed in real-world data. We validate the model using data from the Social Evolution dataset of the MIT Human Dynamics Lab describing changes in friendships and health self-perception in a targeted student population over a nine-month period. We demonstrate the effectiveness of the approach by predicting changes in both opinion spread and connectivity of the network. We also use the model to evaluate how the network parameters, such as the level of ‘openness’ and willingness to incorporate opinions of neighboring agents, affect the outcome. The model not only provides insight into the dynamics of ever changing social networks, but also presents a tool with which one can investigate opinion propagation strategies for networks of various structures and opinion distributions.

Keywords: Agent-based, social network, opinion dynamics, connectivity dynamics, data-driven

1 Introduction

People in real-world societies interact with each other, and as a result, change both their opinions and social connections. Understanding and predicting these changes is crucial in applications such as predicting disease spread [21], understanding rumor propagation through the societies [18], and organizing marketing campaigns [13]. Social networks are often modeled as graphical structures of connected agents along with their opinions. The agents of a network interact with each other stochastically and can change both their opinions and connections, often forming clusters of more tightly connected agents.

The literature dedicated to modeling social networks well represents various dynamics used to simulate agent interactions [1, 2, 5, 7, 14, 19]. However, much of the literature is dedicated to models that either focus solely on the update of opinions [1, 5, 7, 19] or on the update of connections [9, 12, 14, 15]. In real-world networks it is often the case that both opinions and connections of agents change over time. To reflect such complexity, we propose a social network modeling approach that incorporates changes and observed dynamics of both opinions and connections, and is based on assumptions developed through real-world data observations. Using data from the Social Evolution Dataset of the MIT Human Dynamics lab [16], we show that the social network of students based on both self-reported friendships and opinions on a number of subjects such as health self perception exhibits both opinion and connection change over time. Additionally, we observe that the network creates clusters of more interconnected people whose opinions become more homogenized with time.

Some of the existing work using The Social Evolution Dataset [16] concentrated on tracking the evolution of social relationships using frequency of interactions [25], focusing on the importance of face-to-face interactions in causing opinion change [3], and analyzing the correlation between the duration of exposure to certain opinions and the adaptation of those opinions [4]. We extend this analysis by incorporating findings in a more general model of interactions between subjects, namely, reflecting the overall trends in opinion and connectivity over time as observed in the data. We analyze the effect of cluster formation on opinion propagation. The creation of such clusters, caused by temporal updates in connectivity of the network, has been shown to naturally form in societies [9, 12, 15], and has been observed in the data. Several studies have accounted for clustering in social networks as a result of varied strength of social ties [2, 15]. We follow this trend by using

clusters as a measure of the strengths of connections between agents.

The model provides insight into the dynamics of ever changing social networks, as well as presents a tool with which one can investigate opinion propagation strategies for networks of various structures and opinion distributions.

2 Social Evolution Dataset

2.1 Data Description

We use the Social Evolution Dataset of the MIT Human Dynamics Lab [16], which details a study of students living in a Harvard dormitory. The students¹ were surveyed five times over the course of eight months and asked to self-report their perceptions of various aspects of their lives such as their health, their weekly hours of exercise, political opinion, and number of fruits and vegetables consumed weekly as well as to indicate their close friends and socializing partners in the dormitory. The number of students varied from 65 in the first survey to 60 in the last. There was no demographic data such as age and gender of the students accompanying the surveys. We use data from five survey times: September 2008, October 2008, December 2008, March 2009, April 2009, denoted as: 2008.09, 2008.10, 2008.12, 2009.03, and 2009.04 respectively. In further discussion, we use the part of the survey covering each student’s opinion of his or her own health (referred to as “health opinion”) and self-reported list of close friends.

Health opinion as recorded in the survey could take one of five values: 2 (healthy), 1 (average), 0 (below average), -1 (unhealthy), and -2 (very unhealthy) and could be changed upon the completion of each new survey. For modeling purposes we will use a value in the continuous range $[-2, 2]$ reflecting health opinion. Figure 1 shows the change in both health opinion and friendships over time from the survey data, where each node represents a student². The connections in the graphs correspond to the friendships between students as indicated in the surveys. The edges are directed because in the data, friendship is not necessarily reciprocal (if student A considers student B a friend, student B does not necessarily consider student A a friend). The colors in the graphs correspond to the self-perceived health values reported by the students. As reflected in

¹One student, (28 in the data) was a significant outlier and thus not considered in the study.

²The graphs shown were produced using a force directed layout as documented by the JUNG library [20].

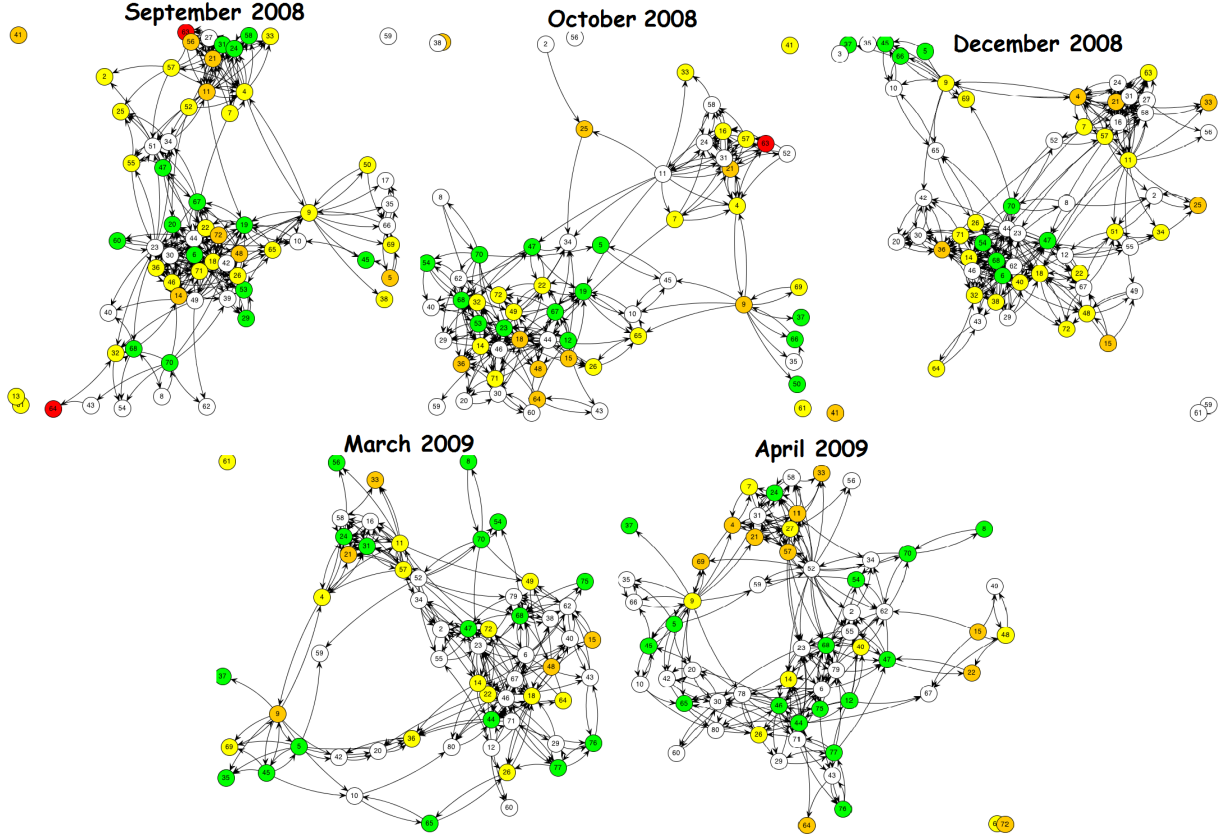


Figure 1: The network representation of survey data. Each student is represented as a node in the graph; friendships are shown by directed edges. Colors reflect node opinion: healthy (green), average (white), below average (yellow), unhealthy (orange), very unhealthy (red). Note the prominent changes in opinion distribution and connectivity of the network over time.

the graphs, students change both their opinions and friendships between surveys, as well as form distinct clusters. The tendency for agents in social networks to naturally form clusters was observed in several studies [9, 15, 12].

Below we discuss an approach to identify clusters in the network. There we use an undirected version of the graph³ in order to increase the performance of the clustering algorithm and produce more dense clusters.

2.2 Cluster and Data Evaluation Metric

We analyzed dynamic trends in the average opinion and connectivity of clusters in the student network. We define clusters, highly interconnected groups of agents that share few connections with the rest of the network, using a variant of the algorithm proposed by Girvan and Newman

³If both edges (i, j) and (j, i) exist in the directed graph, then i and j are connected by an undirected edge. Otherwise, no edge exists between i and j in the undirected version.

[11] as implemented by the JUNG library [20]. We determine the optimal set of clusters based on the following metric, m , proposed by Schaeffer [23, pg. 38]:

$$m = \frac{deg_{int}}{deg_{int} + deg_{ext}}, \quad (1)$$

in which deg_{int} is the number of edges connecting two nodes within the given cluster and deg_{ext} is the number of edges connecting a node within the given cluster to a node outside the given cluster. The metric implies that in a high quality cluster⁴, nodes share many connections with each other and few connections with the rest of the network. Using (1), we compute the average quality of each set of clusters produced by the clustering algorithm, and select the best subset based on the highest average value of m . The defined optimal set is used in further analysis.

Let the nodes in cluster C of size k be c_1, c_2, \dots, c_k and have opinions $o(c_1), o(c_2), \dots, o(c_k)$ respectively. For each cluster, we introduce the following measures:

Cluster Opinion: We define cluster opinion, $O(C)$, as the average opinion of the nodes in the cluster:

$$O(C) = \frac{\sum_{1 \leq i \leq k} o(c_i)}{k}. \quad (2)$$

Opinion Spread: We define opinion spread, $S(C)$, as a measure of how far, on average, the opinions of the nodes in the cluster are from the cluster opinion:

$$S(C) = \frac{\sum_{1 \leq i \leq k} |o(c_i) - O(C)|}{k}. \quad (3)$$

Inner Connectivity: We define the inner connectivity, $I(C)$, of a cluster as the number of edges in the cluster divided by the number of possible edges:

$$I(C) = \frac{|E|}{k(k-1)}. \quad (4)$$

Where $|E|$ is the number of directed edges in the cluster.

⁴We define a cluster as a set of nodes with size greater than 2. Throughout the paper, only clusters satisfying this property are considered in our modeling and analysis

2.3 Data Observations

We cluster the network at each of the five survey times and for each survey time, compute the average value of the proposed cluster metrics. The results are summarized in Table 1, reflecting trends on both opinion and connectivity change over time.

	2008.09	2008.10	2008.12	2009.03	2009.04	trend	p-val
Cluster Opinion	.57	.67	.68	1.03	1.02	increases	.00402
Opinion Spread	.87	.77	.66	.59	.52	decreases	.00176
Inner Connectivity	.48	.60	.63	.65	.66	increases	.03986
Avg. Cluster Size	8.20	7.12	5.67	4.60	4.67	decreases	.00456

Table 1: The observed changes in clusters for each survey time. The values in the table are the averages of each metric over all clusters for each time set.

Trend observations were validated with a one-tailed linear regression t -test with time as the independent variable and the cluster metric as the dependent variable. As the average cluster size decreases over time, the connectivity within cluster increases, and opinions become more uniform. We observed an overall increase in the value of health self-perception over time:

Observation 2.1: The average cluster opinion significantly increases over time ($p = .00402$).

Observation 2.2: The average opinion spread of the clusters significantly decreases over time ($p = .00176$).

Observation 2.3: The inner connectivity significantly increases over time ($p = .03986$).

In addition to Observation 2.1, analysis of individual opinions showed a pronounced tendency towards moving away from both the extreme negative opinion (-2) and the neutral one (0) as seen in Figure 2. In 2008.09 there were 22 students with opinion 0 while in 2009.04 there were only 8 such students. Furthermore, by 2009.04, 42 students adopted positive opinions while only 10 students adopted a negative opinion. The movement away from negative opinions towards positive ones is further supported by the fact that in 2009.04, there are 0 students with opinion -2, the most extreme negative opinion, while there are 16 students with opinion 2, the most extreme positive opinion. The model proposed in the next sections takes these observations into account (see section 3):

Observation 2.4: Individual opinions tend to move away from the neutral opinion value. The observed shift in positive direction is more significant than that in the negative direction.

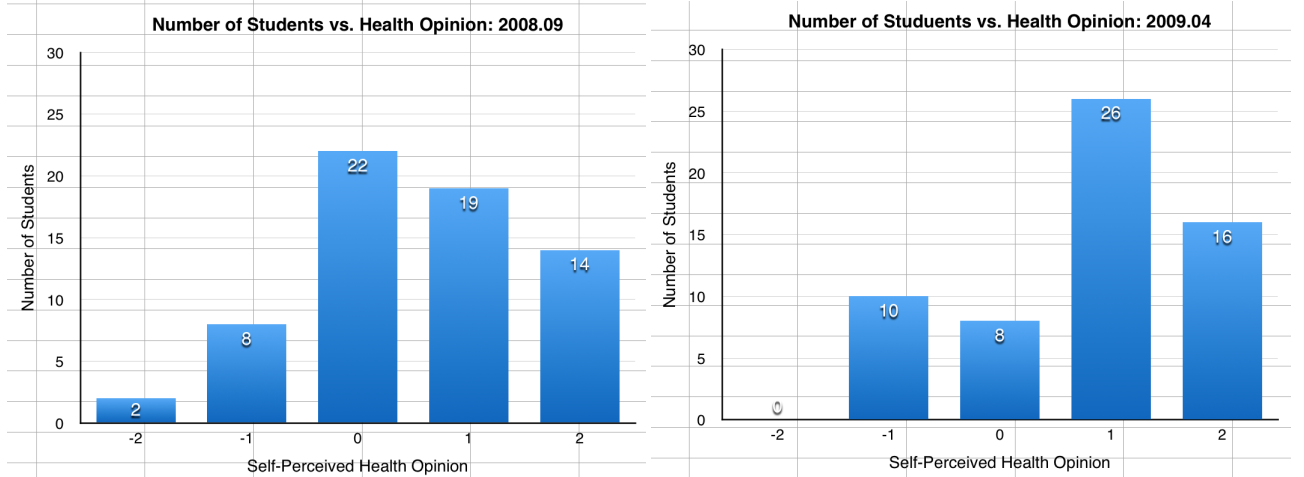


Figure 2: Histogram of self-perceived students’ health for survey times 2008.09 (left) and 2009.04 (right). Note the significant deviation away from 0, the neutral opinion value, towards more opinionated values such as -1, 1, and 2. The number of agents that reach strong positive opinions (opinions of 1 and 2) is significantly higher than the number of agents that reach strong negative opinions (opinions of -1 and 2), suggesting an asymmetric bound

Based on the above-mentioned observations we conclude that in addition to overall tendency to move opinion in a more positive directions, students have a tendency to ‘amplify’ their opinion. Particular enhancement of opinion is observed when it falls within $(-1, 0) \cup (1.5, 2)$. This range of values and observed asymmetry will be used in model simulations (see section 4).

3 Agent-Based Model of the Dynamic Network

Using observations from data, we develop an agent-based model [6, 15] aimed at both recreating and predicting the trends in both cluster opinion and connectivity observed in Social Evolution Dataset (section 2). The model implements the changing of both opinions and connections via a stochastic process, in which the state of the network at time $t + 1$ is determined by the state of the network at time t .

3.1 Structure of the Network

Define the network at time t as a directed graph $G(N, A_t)$ with set of nodes N and adjacency matrix A_t , denoting friendships between agents. Each node i in the network is an agent having an opinion $o_i(t)$ at time t .

As observed in the data, A_t can be asymmetric. In addition, several studies have demonstrated that social ties often have unequal strength [2, 15]. We define the difference in strengths of con-

nections between nodes through cluster memberships, so that connections between nodes within a cluster are stronger than those between nodes from different clusters. Using this concept, we define A_t as follows:

$$a_{ij}(t) = \begin{cases} 0 & \text{if no edge connects node } i \text{ to node } j \text{ (no } i \text{ to } j \text{ friendship),} \\ 1 & \text{if } i \text{ is connected to } j \text{ from a different cluster (} i \text{ befriends } j \text{),} \\ w \ (w \geq 1) & \text{if } i \text{ is connected to } j \text{ from the same cluster (} i \text{ befriends } j \text{),} \end{cases} \quad (5)$$

where $a_{ij}(t)$ denotes row i , column j of A_t . The parameter w reflects the strength of cluster effect (i.e. how much stronger friendships are between agents in the same cluster versus between agents in different clusters).

3.2 Opinion Update

At each time t , agents interact with each other through existing friendship connections. As a result, each node's opinion is updated according to the influence exerted by its friends. In particular, we assume that interaction with friends affects opinion change, and that a friend's influence is stronger if both agents belong to the same cluster. We also take into account the opinion amplification effect discussed in Section 2.

Let $q_i(t)$ be the influence that agent i 's friends exert on agent i 's opinion, $o_i(t)$:

$$q_i(t) = \sum_{j \in N} (\alpha) \frac{a_{ij}(t)}{\sum_{k \in N} a_{ik}(t)} (o_j(t) - o_i(t)), \quad (6)$$

where $\alpha \in (0, 1]$ is a slow learning scale factor [19]. The equation reflects the assumption that all the friends affect the agent's opinion, but that the effect is proportional to the strength of connection between agents.

In addition, we take into account the tendency of agents to amplify their opinions towards a more extreme value. As noted in Observation 2.4 and supported by [8, 10], opinions in social networks tend to radicalize toward more extreme values over time. In other words, the longer an agent possesses any given opinion, the stronger that opinion becomes. We introduce an opinion

amplification function, $s(y)$ to reflect this observation:

$$s(y) = \begin{cases} ky \ (k \geq 1) & \text{if } y \in D, \\ y & \text{otherwise,} \end{cases} \quad (7)$$

where D is an empirically defined domain of opinions in which such amplification takes place and k is a parameter representing the extent to which agents have a natural tendency to amplify their opinions over time.

Taking (6) and (7) into account, we define the opinion $o_i(t+1)$ of every agent i as follows:

$$o_i(t+1) = s(o_i(t) + q_i(t)). \quad (8)$$

3.3 Connection Update

The update of connections follows the update of opinions from time t to time $t+1$. After the update of opinions, each node will probabilistically form one connection and probabilistically break one connection using the following assumptions:

3.3.1: Agent i can form friendships with friends of its friends [12, 15]

3.3.2: Agent i can form friendships with agents that already consider him a friend [9, 12, 24].

3.3.3: The stronger the potential connection between two disconnected agents, the more likely the connection is to form [2, 15]. In terms of our model, a connection between agents within the same cluster is more likely to form.

3.3.4: The stronger the connection between two connected agents, the less likely the connection is to break [17]. In terms of our model, a connection between agents in the same cluster is less likely to break.

We define S_f as a set of edges that could form, and S_b as a set of edges that could break. By definition, $S_f \cap S_b = \emptyset$.

Define probability $f_{ij}(t)$, the probability that a directed connection from i to j forms between times t and $t+1$, and $b_{ij}(t)$, the probability that a directed connection from i to j breaks between

times t and $t + 1$ as follows:

$$f_{uv}(t) = \begin{cases} \beta p_{ij}(t) & \text{if } (i, j) \in S_f, \\ 0 & \text{if } (i, j) \notin S_f, \end{cases} \quad (9a)$$

$$b_{ij}(t) = \begin{cases} \beta(1 - p_{ij}(t)) & \text{if } (i, j) \in S_b, \\ 0 & \text{if } (i, j) \notin S_b, \end{cases} \quad (9b)$$

respectively, where $\beta \in (0, 1]$, and $p_{ij}(t)$ is:

$$p_{ij}(t) = \begin{cases} (.5 - c) & \text{if } i \text{ and } j \text{ are not in the same cluster,} \\ (.5 + c) & \text{if } i \text{ and } j \text{ are in the same cluster,} \\ (.5) & \text{if } j \text{ is in not in any cluster} \end{cases} \quad (10)$$

The parameter $c \in [0, .5)$ represents the extent to which agents restrict their friendships to those within their own cluster. Function $p_{ij}(t)$ accounts for the assumption that connections are more likely to form and stay within clusters rather than between clusters. Using (9a), (9b), and (10), we update the adjacency matrix from A_t to A_{t+1} using the Monte Carlo method [22]. The network is then re-clustered using the algorithm in section 2 and A_{t+1} is updated again according to (5).

4 Results

4.1 Modeling and Predicting Network States in the Social Evolution Dataset

In this section, we apply the proposed model to the Social Evolution Dataset in order to demonstrate the model's effectiveness in replicating the observed trends of both opinion spread and connectivity. We use the earlier defined measures of cluster opinion, opinion spread, and inner connectivity in order to compare model results with the observed data. We recreate the short term trends observed in the data, and extend projections to future states thus anticipating longer-term network dynamics.

In application to the Social Evolution Dataset we define D from (7) as $(-1, 0) \cup (1.5, 2)$ (see

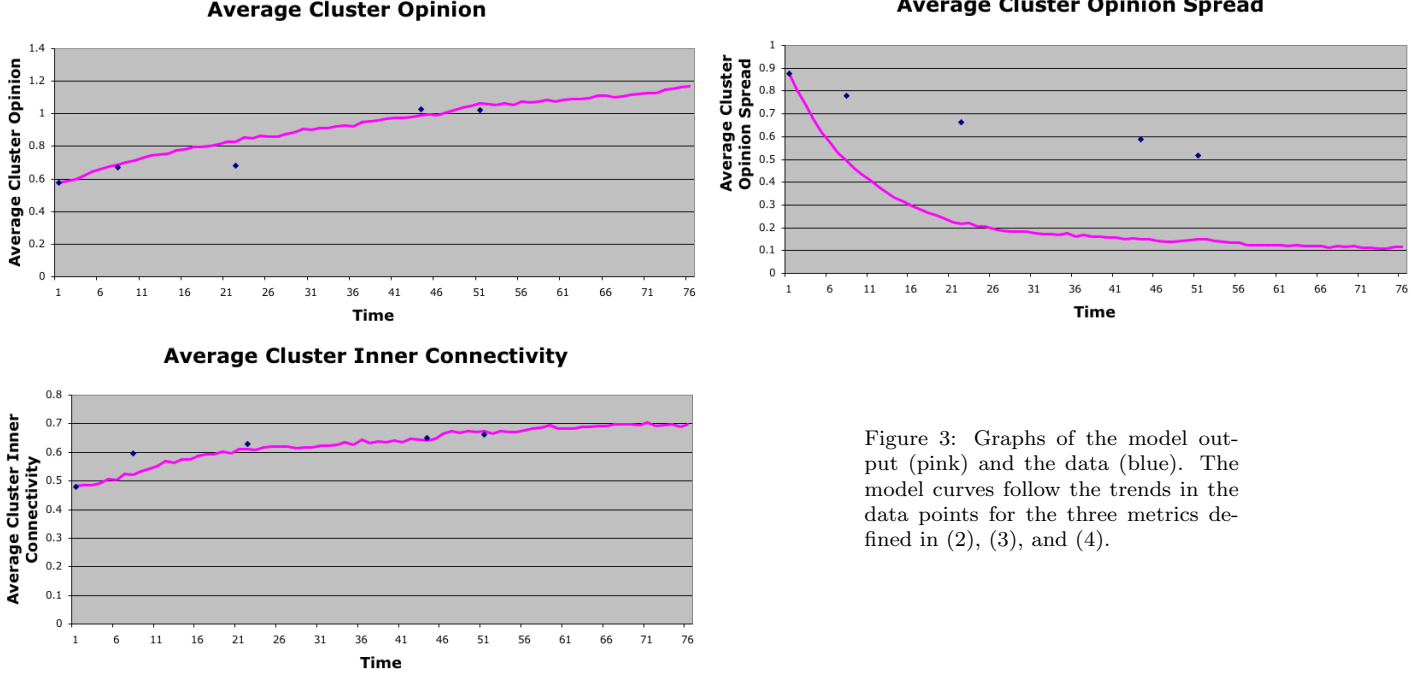


Figure 3: Graphs of the model output (pink) and the data (blue). The model curves follow the trends in the data points for the three metrics defined in (2), (3), and (4).

Observation 2.4). We also bound opinion values produced by (7) to $[-2, 2]$ in accordance with data (section 2), setting any value less than -2 or greater than 2 to -2 and 2 respectively.

The model has three parameters: w (tendency to follow the opinion of those from the same cluster versus those from a different cluster), k (tendency to radicalize opinion), and c (tendency to form more friendships with those from the same cluster versus with those from a different cluster), along with two scalars, α and β , which regulate the rate of opinion and connection change respectively. Using the network from the first survey time in our data (2008.09) as an initial condition ($t = 0$), we ran simulations in order to identify values for the parameters that best describe the social network dynamics of the data.

Figure 3 shows the results of simulations using parameter values $w = 5$, $k = 1.05$, $c = .245$ and scalar values $\alpha = .10$, $\beta = .15$ (pink curve), which were selected for providing the best fit to the data (shown as the blue points). The results shown are the average over 50 simulations.

The accuracy of the model was evaluated using the percent error⁵. Cluster opinion had an average percent error of 7.07% and inner connectivity had an average percent error of 5.22%, thus indicating that the model is accurate within a reasonable error bound in predicting the trends in these two metrics. The opinion spread generally followed the observed trend, though the percent

⁵percent error = $\frac{|\text{model value} - \text{data value}|}{\text{data value}} * 100\%$

error was significantly larger. Note that while the model's prediction of cluster opinion closely followed the data trend, the opinion spread decreased more quickly in the model than in the data. This means that the average opinion of the clusters in the model changed at the same rate as the average opinion of the clusters in the data but the opinions of the agents in each cluster converged to the average opinion of the cluster faster in the model than in the data.

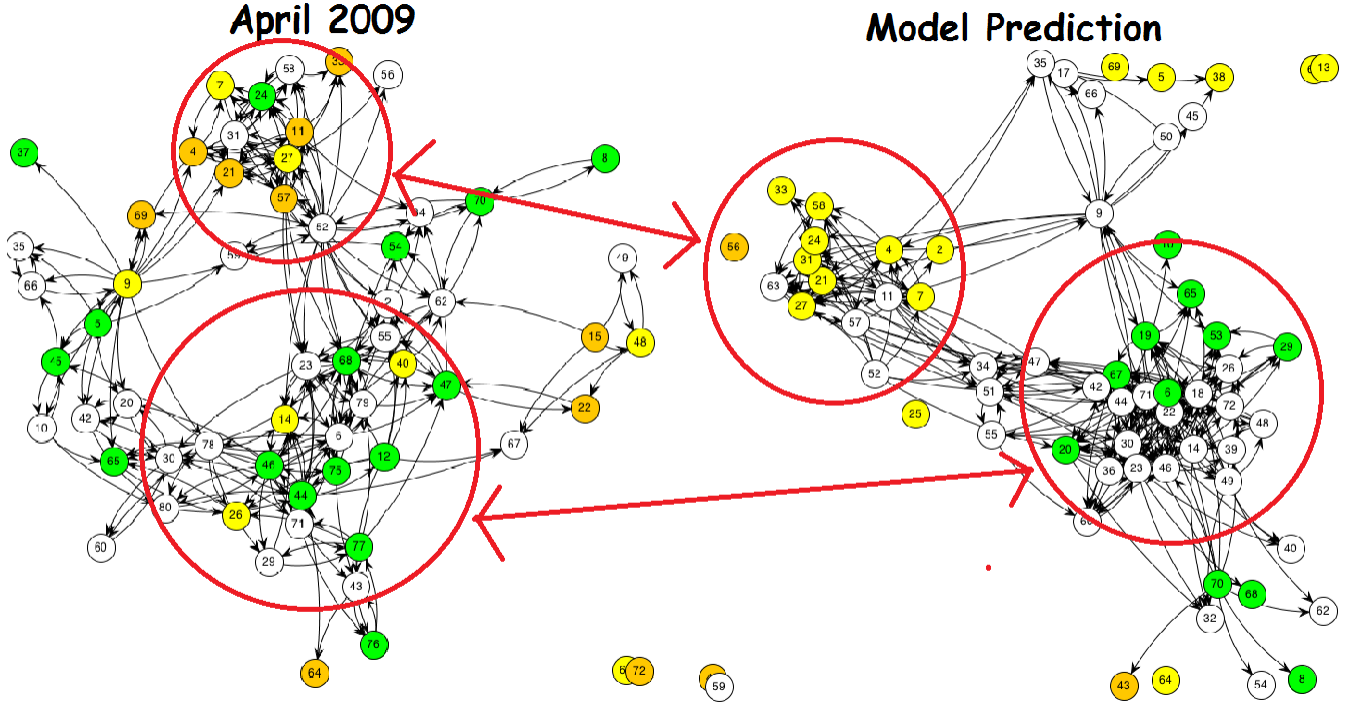


Figure 4: The data at 2009.04 (left) and the model at $t = 50$ (right). Note the similarity between the two networks in the existence of a larger cluster that is mostly green (opinion value 2) and white (opinion value 1) and a smaller cluster that is mostly yellow (opinion value 0) and orange (opinion value -1). Visuals created with assistance of code from the JUNG library. [20]

At $t=50$ in the simulations, the average opinion in the model is close to 1.0 and the average inner connectivity is close to .65 (Figure 3). These values are close to those observed in 2009.04 survey, the last survey in the data (see Table 1). Figure 4 further demonstrates the similarity between the network output at $t = 50$ and the data in 2009.04. Note the similarity of the two networks in the existence of two prominent clusters, one containing agents with positive opinions (white and green) and one containing agents with neutral and negative opinions (yellow and orange).

Figure 5 shows longer term simulation results using the same initial conditions and set of parameters. As time increases, the average cluster opinion spread approaches 0, which suggests

that with this set of parameters, the opinions of nodes in individual clusters will converge to the same value, between 1.5 and 2 (Figure 5).

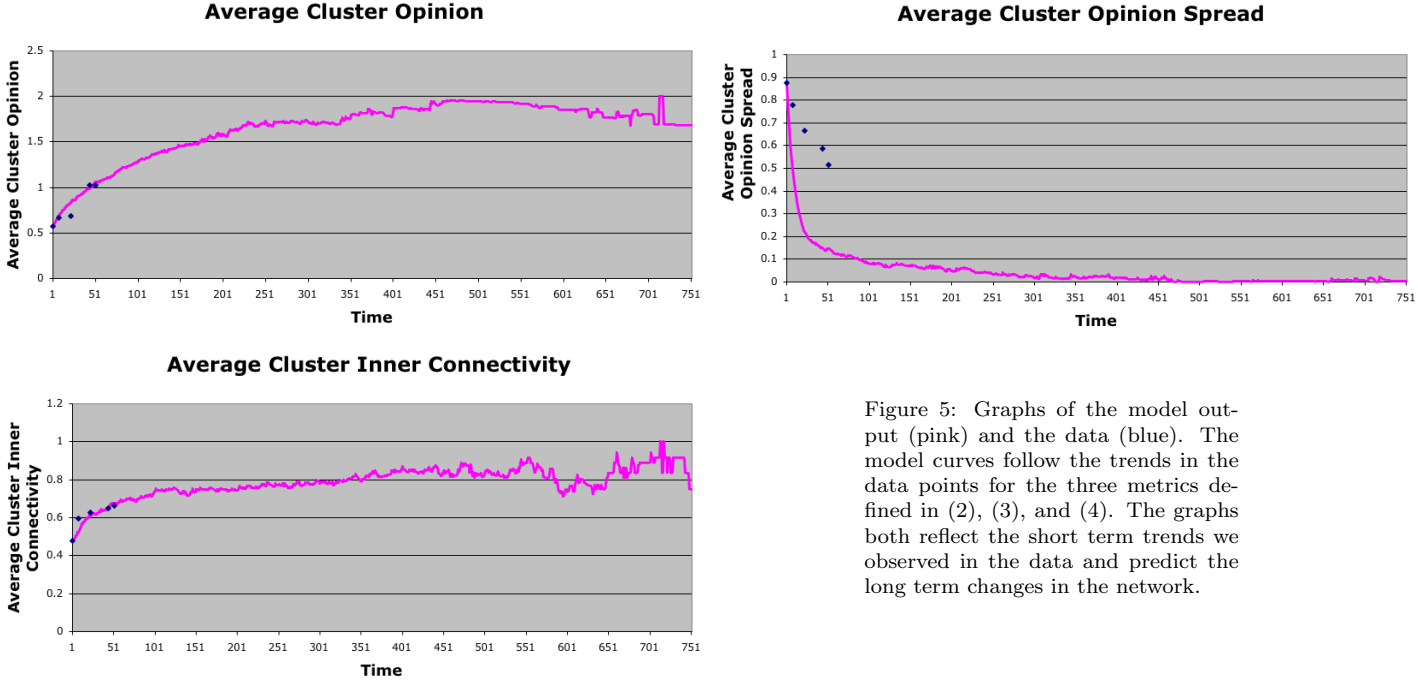


Figure 5: Graphs of the model output (pink) and the data (blue). The model curves follow the trends in the data points for the three metrics defined in (2), (3), and (4). The graphs both reflect the short term trends we observed in the data and predict the long term changes in the network.

4.2 Network Dynamics Under Varying Social Conditions

The parameters in the model represent a number of aspects of society such as tendency to follow the opinion of those from the same group (cluster) versus those from a different group (parameter w), tendency to amplify (‘radicalize’) opinion (parameter k), and tendency to form new friendships with those from different groups rather than the same group (parameter c). We vary the parameters in order to gain an understanding of how the network dynamics change under different sets of conditions governing interactions between agents.⁶

We use the first survey data (2008.09) as the initial condition for the model at time $t = 0$ and vary only one parameter at a time in order to avoid the confounding effects. Note that varying w and k only affects changes in cluster opinion and opinion spread as these two parameters have no effect on the changing of connections. When varying c , changes are observed in the inner connectivity of clusters, followed by changes in cluster opinion and cluster opinion spread.

⁶Note however, that we do not consider the constants α and β parameters. Instead, they are data-driven constants used to control the speed at which opinion and connection update respectively occur for which the values $\alpha = .10$ and $\beta = .15$ were confirmed in subsection 4.1.

4.2.1 Clustering effect on opinion change

Giving preference to agents in the same cluster does not affect the long-term average opinion and opinion spread past a certain degree of preference. However, a low degree of preference significantly affects a rate of convergence to long-term cluster opinion (see Figure 6).

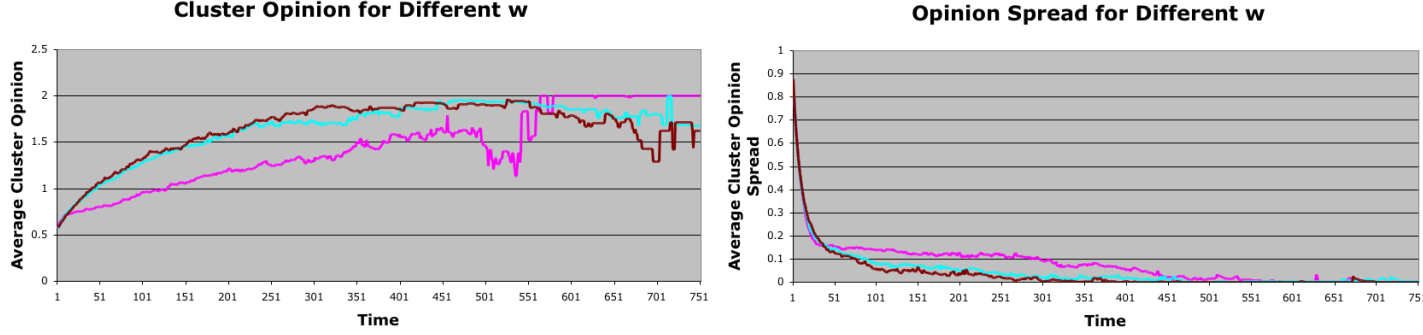


Figure 6: Average cluster opinion (left) and average cluster opinion spread (right) for $w = 1$ (pink), $w = 5$ (blue), and $w = 100$ (brown). We hold $c = .245$ and $k = 1.05$ constant. Note that as w increases, the differences between the three curves in long term average cluster opinion becomes negligible, thus suggesting that weighted friendships only affect long term opinion propagation up to a certain point.

4.2.1.1: For large values of w , there is no observable difference in both long-term opinion dynamics and opinion spread dynamics (Figure 6).

High values of w indicate that agents are influenced to a greater degree by agents within their cluster than by those outside one. We ran 50 simulations each for 5 different values of $w > 1$ between 5 and 100 (with $w = 5$ and $w = 100$ shown in Figure 6) and observed a convergence within 12.5% after 50 iterations. We conclude that given that agents follow the opinions of friends within their own cluster ($w > 1$) more, the degree to which they do so does not significantly impact cluster opinion and cluster opinion spread in the long run.

4.2.1.2: A slower rate of change occurs in both average cluster opinion and opinion spread when agents have no tendency to favor the opinions of their cluster members over the opinions of the rest of the network ($w = 1$).

When $w = 1$, all agents in the network have an equal influence on any given agent's opinion, regardless of the clusters they belong to (equations (5) and (6)). As discussed in Section 2, the average cluster opinion of the network is initially positive, with more agents having positive opinion than negative one. In combination with amplification effect (see (7)) this leads to a slow increase in the average opinion value over the network, surpassing the effect of negative amplification.

4.2.2 The tendency to amplify (‘radicalize’) opinions

When varying opinion amplification parameter k , we analyzed the effect of amplification of opinion (‘radicalization’) on overall network opinion and opinion spread.

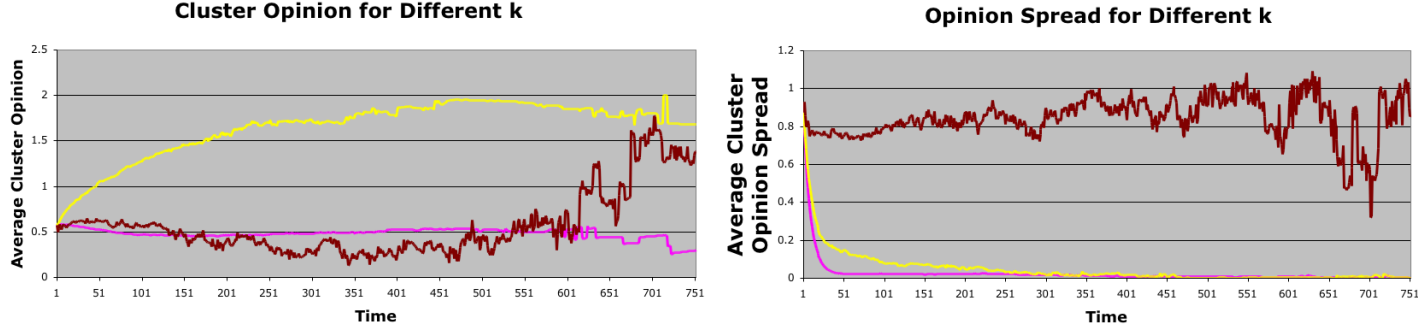


Figure 7: Average cluster opinion (left) and average cluster opinion spread (right) for $k = 1$ (pink), $k = 1.05$ (yellow), and $k = 2.00$ (brown) while holding $c = .245$ and $w = 5$ constant. Note the long term instability of the curves for $k = 2.00$ which results from very large opinion amplification.

4.2.2.1: Average network opinion remains fairly constant and opinion spread decreases most rapidly when agents have no tendency to amplify opinions ($k = 1.00$).

With no opinion radicalization, agents’ opinions are not pulled away from the average opinion of the network towards more extreme opinion values. Therefore, the average cluster opinion remains fairly constant and the opinions of agents in the network converge towards the average very quickly.

4.2.2.2: Average network opinion increases significantly and opinion spread decreases more slowly when agents have a slight tendency to radicalize opinions ($k = 1.05$).

When $k = 1.05$, there is a slight radicalization of opinions. From the bounds we implement on the amplification function in (7), we know that positive opinions are favored over negative opinions. Therefore, the amplification of negative opinions is not enough to offset the amplification of positive opinions, resulting in an increase in average opinion. However, the fact that there is a slight amplification in the negative direction as well as in the positive one causes the opinion spread to decrease more slowly as the opinions in the network are pushed away from the average.

4.2.2.3: Average opinion and opinion spread are very unstable when agents have a very high tendency to radicalize opinions ($k = 2.00$).

The amplification function defined in (7) affects both positive and negative opinions for high values of k . As a result of probabilistic interactions with their neighbors, the agents’ opinions are randomly pulled in both positive and negative directions. As opinions become increasingly

amplified with time, the random swings become stronger, resulting in significant fluctuations of opinion seen in Figure 7.

4.2.3 Increase of connectivity within clusters

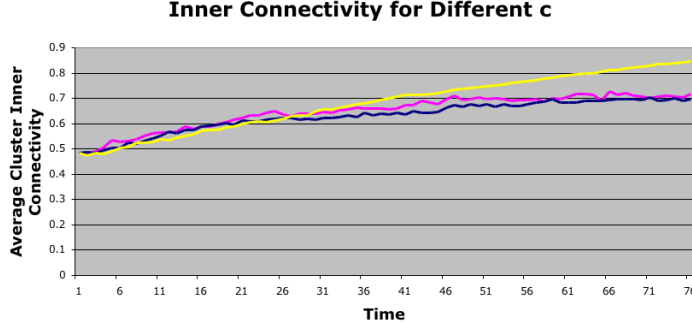


Figure 8: Average cluster inner connectivity for $c = 0$ (pink), $c = .245$ (blue), and $c = .49$ (yellow) with $w = 5$ and $k = 1.05$ held constant. Note that the curves for $c = 0$ and $c = .245$ level off long term while the curve for $c = .49$ tends to increase rapidly.

Parameter c reflects the tendency of agents to connect with their own cluster over the rest of the network. We ran simulations with five different values of c . Figure 8 shows the change in inner connectivity over time for three of the values, $c = 0$, $c = .245$, and $c = .49$. There is no observed change in connectivity levels within clusters for $c = 0$ and $c = .245$, while inner connectivity significantly increases for $c = .49$. This leads to a different dynamics of opinion change.

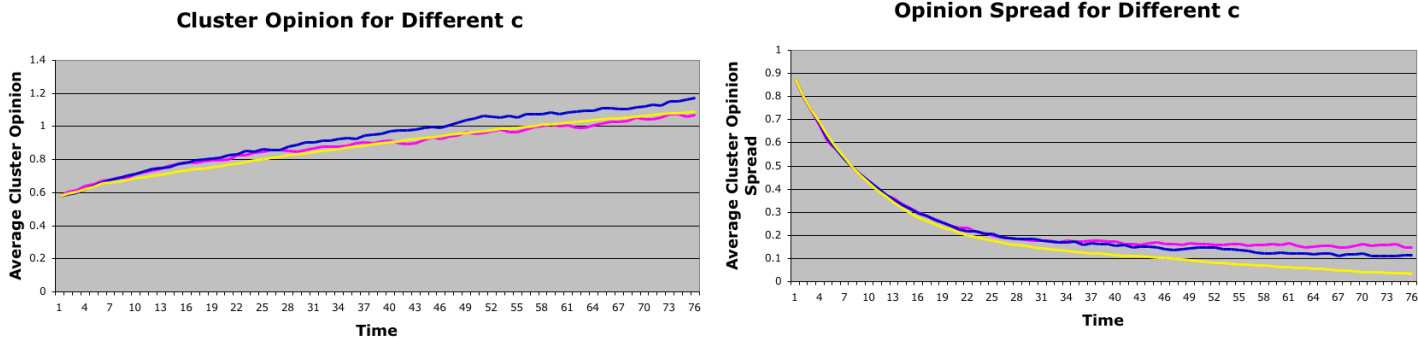


Figure 9: Average cluster opinion (left) and average cluster opinion spread (right) for $c = 0$ (pink), $c = .245$ (blue), and $c = .49$ (yellow) while holding $w = 5$ and $k = 1.05$ constant. Note that as c increases, average cluster opinion spread decreases more quickly while no clear trend is observed in average cluster opinion over a long period of time. The difference observed in cluster opinion spread but not in cluster opinion suggests that agents in a more interconnected cluster tend to the same opinion more quickly, but what opinion the agents tend towards is not affected by the interconnectedness of the cluster.

4.2.3.2: As agents' tendency to connect with their own cluster increases, average cluster opinion spread decreases more quickly but cluster opinion is not significantly affected.

By equation (6), a more interconnected cluster means that a given agent will be influenced by the opinions of a greater number of agents within its cluster, or in other words, there will be more

interactions between agents of a given cluster. As a result of the greater number of interactions, the opinions of agents within a cluster will converge towards a similar value more quickly (Figure 9). Although c influences the number of opinion updates between agents, it does not influence the nature of those interactions. Therefore, the network will tend towards the approximately the same average cluster opinion for different values of c , but at different rate.

5 Conclusion

We have developed an agent-based social interactions model incorporating temporal changes in both opinion and connectivity through local interactions. The model successfully replicated observations from a real-world MIT Human Dynamics Lab dataset [16] containing surveys of a student population. We have identified parameter values with which we were able to reproduce general trends observed in both opinion and connectivity in data from a student network. In addition, we used the model to forecast the longer term dynamics of the observed network. We demonstrated that in order to accurately reflect trends from data, one needs to take into account not only opinion influence and interchange in the student population, but also changes in network structure reflected in the model as connections between nodes.

We analyzed the effect of group membership on opinion change. When varying w , the extent to which weighted friendships due to clustering affects opinion change, we observed that weighted friendships between agents only affects long term opinion propagation up to a certain point, beyond which the long term opinion propagation changes negligibly. When $w = 1$, meaning that agents are equally influenced by all those they are connected to regardless of cluster membership, average cluster opinion increases more slowly than when $w > 1$ and average cluster opinion spread decreases more slowly than when $w > 1$.

When varying k , the extent to which opinions in a human society ‘radicalize’, we noted that a small increase in tendency to radicalize results in an increase in long-term average cluster opinion and a slower decrease in opinion spread, while a large increase in tendency to radicalize results in long-term instability in both cluster opinion and opinion spread.

Lastly, we observed that when the tendency of agents to restrict their friendships to those within the same cluster increases (with higher values of c), the average inner connectivity of the clusters

increases more quickly over time. We also found that as clusters become more interconnected, the opinions of agents in each cluster tend to converge to the same value at a faster rate.

The model created yields not only a method for reflecting the dynamics of and predicting the changes in a real human society, but also tools both for studying the changes that occur in various theoretical networks and for gaining insight into methods for manipulating the changes in these networks for societal benefit.

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